Multistep Detection of Oriented Structure in Complex Textures

Estelle Parra-Denis, Michel Bilodeau, Dominique Jeulin

MULTISTEP DETECTION OF ORIENTED STRUCTURES IN COMPLEX TEXTURES

E. Parra-Denis[1], M. Bilodeau[1] and D. Jeulin[1]

1 Mines ParisTech, CMM-Centre de Morphologie Mathématique, Mathématiques et Systèmes, 35 rue Saint Honoré ,77305 Fontainebleau cedex, France

ABSTRACT

In the context of online industrial control, we propose a multistep method, based on mathematical morphology operators, to carry out the characterization of oriented structures in a complex texture environment. In a data base of about ten thousand patches, ten percent show various oriented structures.

First we measure for each patch the x and y covariances, and apply pyramids of dilations-erosions and openings-closings using linear structuring elements. Second we transform the resulting pyramid images into usable condensed information. All the measures for each patch set up texture descriptors. For each of them we apply a Principal Components Analysis (PCA) to sum up the information. Then we use a Linear Discriminant Analysis (LDA) on the principal axes which carry the most information and analyze in the LDA space the distribution of the two types of patches to reach 99.45% of sensitivity and 99.61% of specificity.

KEYWORDS: Mathematical morphology, texture analysis, online control, oriented signatures

I. INTRODUCTION

In industrial processes, intelligent visual inspection systems to ensure the quality in production lines are more and more used [1]. The raw materials have to be controled to guaranty the property of the final product. The automation problems for inspection can be divided into two main categories. The first category relies on uniform material such as metals, papers… On these materials defect detection corresponds to identify regions that differ from a uniform background [2][3][4]. The second category is related to textured materials such as textiles, ceramics… The texture defect varies from sample to sample and a hierarchy of defects has to be defined [5]. The study proposed in this paper corresponds to the second category, identification of foreign structures on a textured background. A good overview of all the methods can be found in [6].

In this paper, we propose a methodology based on mathematical morphology tools to carry out the detection of oriented structures in a textured background in an online industrial control context.

For the study we have a large data-base of about ten thousand patches, ten percent of them showing various oriented structures within different complex textured backgrounds. These structures are mostly oriented along the two axes of the images (x and y). The images of the data-base are 16 bits grey levels, with a size of 256×256 pixels. Figure 1 shows samples of textured backgrounds from the smoothest to the roughest, while Figure 2 presents different patches of the database showing oriented structures within a complex textured background.

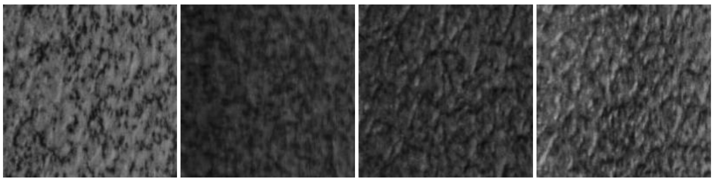

Figure 1 Examples of different texture from the smoothest to the roughest.

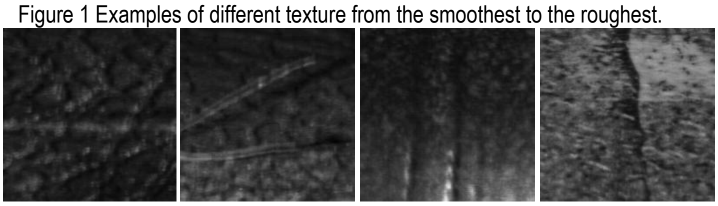

Figure 2 Oriented structures within various textured backgrounds.

This paper is organized as follow. The first part is dedicated to the description of the method used to extract efficient parameters from the patches. We start by explaining the philosophy of our method, in terms of expected results and constraints. Afterward, we present each descriptor in details. The second part deals with the data analysis. Firstly, we use a Principal Component Analysis (PCA) to sum up the measured information into a space of representation. Secondly, we use a Linear Discriminant Analysis to analyze the distribution of the two types of patches. The last part concludes the paper and introduces prospective works.

II. TEXTURE DESCRIPTORS

Method

For an online analysis, we choose operators according to their computational speed as well as their response towards the aim of the study. An online industrial control supposes to be able to give a response on the media quality nearly in real time. The proposed method is multistep. The first step consists in measuring for each patch the x and y covariances, and applying pyramids of dilations-erosions and openings-closings using linear structuring elements of different sizes. The results of the pyramids are images. The second step transforms these images into usable information such as profiles obtained along lines and columns, and extracts textures parameters from the measurements. The third step is to extract from the two profiles (by line and column) condensed information (mean, standard deviation, mean cross value…). We detail in the following each descriptors.

Characterization of random textures

The presence of textured background in a patch suggests the use of a probabilistic approach to characterize its randomness. The texture can be seen as a realization of a random function [7] [8]. In [3] and [9], Cord and al show that characterization tools of random function can be directly used for texture analysis.

In this study, we use the covariance function. It characterizes the distribution of pixels in the space. It is sensitive to nested structures such as clusters, and highlights the presence of periodicity in a patch. The covariance function is defined by equation 1. It corresponds to the measure of the expectation of the image I with itself translated by a vector $\vec{h}$ and by taking away the square of the mean m of I from the obtained result.

$$C(\vec{h}) = E\left(I(x) \cdot I(x+\vec{h})\right) - m^2 \quad (1)$$

$$Cr(\vec{h}) = \frac{C(\vec{h})}{\sigma_I^2} \quad (2)$$

To be able to compare the value of the covariance function from different patches we used the normed covariance (i.e. the autocorrelation function). It corresponds to the ratio of covariance by the variance σ_I^2 of the image I. The obtained descriptors vary between ∓ 1.

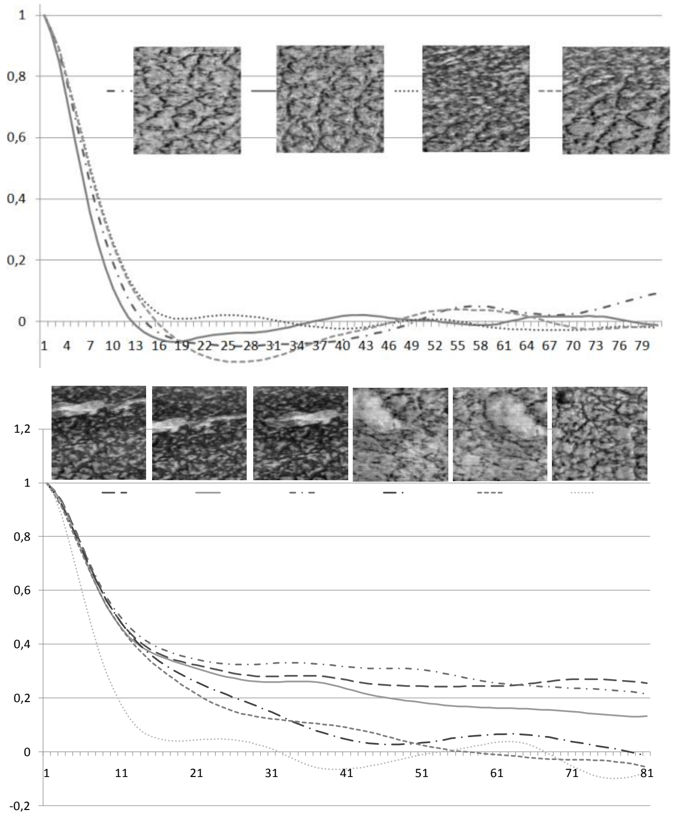

Figure 3 Horizontal auto covariance functions on stationary patches (top) and patches with additional structures (bottom).

Figure 3 shows the covariance functions along x axis for different patches. We can observe the obtained signatures for stationary textured backgrounds are typical. They decrease quickly from 1 to a stage close to 0, which corresponds to the typical length scale (correlation scale) of the medium. When an additional structure is added within the textured patch, it changes a lot the obtained covariance function which at the scale of images is not able to reach its range, especially if the structure is large. We measure for each patch of the database the covariance function along x and y, with translations varying from 1 to 80 pixels (almost a third of the image size).

Statistical texture descriptors

As the structures added to the textured background are mostly oriented along x and y, we estimate a set of statistical measurements along them. First, we measure the difference of the mean line (resp. column) with the global mean. Second, we measure the variance of each line. Figure 4 shows profiles of the mean along lines for different patches. Profiles of homogeneous patches differ from profiles of patches containing directional structures. Each signature has the length of the patch. For stationary textured backgrounds the signal is periodical and more or less dispersed around zero according to the roughness of the patch; while for patches showing additive structure, the signal is deeply changed. To be able to compare the signature of different patches, we extract from the profiles significant parameters: the standard deviation, the extremes (maximum and minimum), the deviation toward the maximal amplitude defined by equation 3, the mean cross positive and negative values obtained for a fixed threshold equal to $\pm 2 \times standart\_deviation$.

$$D = 2 \times standart\_deviation - |max - min| \quad (3)$$

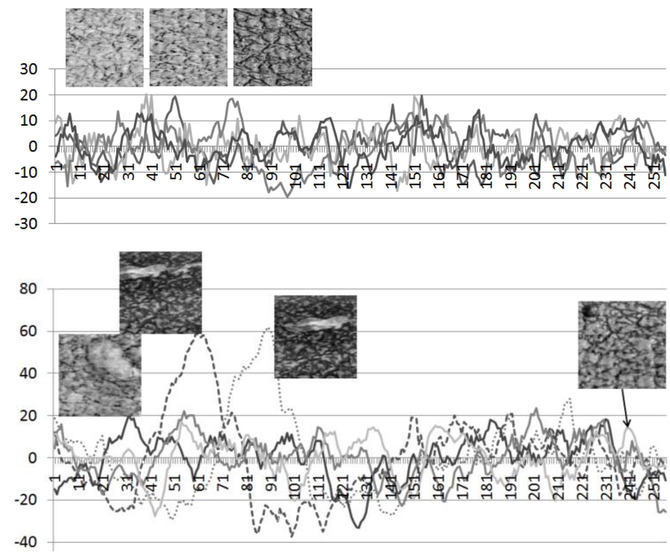

Figure 4 Profile of the difference of the mean line with global mean, top: for textured background, bottom: for structures within textured background.

Morphological filters

The morphological operations such as erosion, dilation, opening and closing are used to study the size distribution in an image. The use of morphological operators to characterize texture had been successively used in [8][4][9][3]. The morphological erosion provides the enhancement of dark structures while dilation provides bright enhancement (Figure 5). We also combine erosion and dilation by using morphological opening and closing (Figure 6). Pyramids of morphological operators allow highlighting dark or bright linear structures oriented along a used structuring element (SE) [10]. In this study since we look for oriented structures along x and y, we use successive linear SE in these orientations. By increasing the SE size, the morphological filters lead to a constant image.

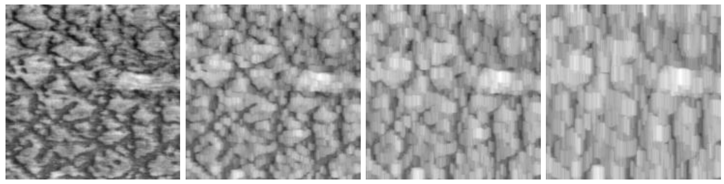
Figure 5 Successive dilations by a vertical SE.

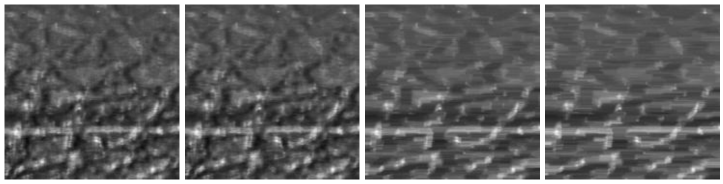
Figure 6 Successive closing by an horizontal SE.

The second step transforms these images into usable information such as profiles obtained along lines and columns using the method explained in the previous section.

For each image patch, the used maximum SE length is 40 pixels; the measures are performed by step two. A set of 1760 parameters is obtained for the pyramid dilation and erosion (resp. opening/closing).

III. RESULTS

For each patch, we obtain a set of descriptors provided on the one hand by the covariance functions along x and y and on the other hand by the pyramids of morphological operators.

Principal Component Analysis (PCA)

For each type of descriptor we use a PCA to sum up the information into a reduced representation space. The PCA considers each patch as a point in a n-dimension space. The value of n corresponds to the number of descriptors used. For example, for the covariance function, we are in an 80 dimensions space. The principle of the PCA is to obtain an approximate representation of this space in a sub-space with a lower dimension by projecting the data cloud on carefully selected axes [3] [11]. These axes are those which maximize the inertia of the projected cloud. The axes are orthogonal. By using this method, it is possible to deeply decrease the number of parameters by just preserving those with the highest variance of the initial values. The covariance is reduced to

3 parameters while pyramids of morphological operators are reduced to 10 parameters. Finally each patch is described by a set of 26 parameters which carry all the measured information.

Linear Discriminant Analysis (LDA)

We use a LDA to analyze the distribution of the two types of patches (with or without oriented structures). The LDA is a supervised data analysis method. It uses the knowledge about the repartition into two classes of patches to create new variables by linear combination of the original variables (obtained as a result of the PCA).

After the analysis of the PCA results, we use the 3 first PCA axes of the covariance functions, and the ten first PCA axes of morphological pyramids. We work in a 26 dimension space. The result of the LDA applied to these 26 PCA axes is presented on Figure 7. The dense cloud on the left corresponds to patches without oriented structured (i.e. with only a textured background). The more disperse cloud on the right corresponds to patches with oriented structures.

By applying this method, on our database we obtain a 99.45% sensitivity and 99.61%specificity. The sensitivity or true positive rate is defined by the ratio of the true positive samples among all detected positive samples available after the LDA. The specificity or true negative rate is defined by the ratio of the real true negative patches among all LDA detected negative patches.

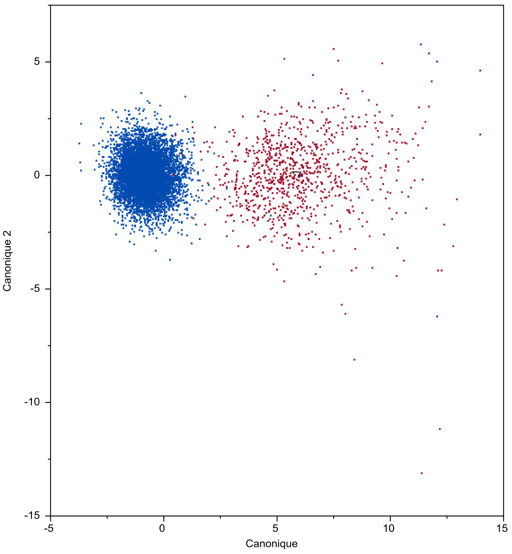

Figure 7 LDA on the principal axes obtained for each descriptor (a point represents a single patch of the data base).

IV. CONCLUSION

This study shows promising results on the used data base for the detection of elongated features in a highly textured background. The presented method allows well separate patches with or without oriented structures. We have to train our method on a larger data base and also on a specific database of this field of research as the one used in [5]. We have to enrich our study, to properly define the performance evaluation toward the textures variability.

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